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Impact of Russian-Ukraine war on energy market: A forecast-based event assessment

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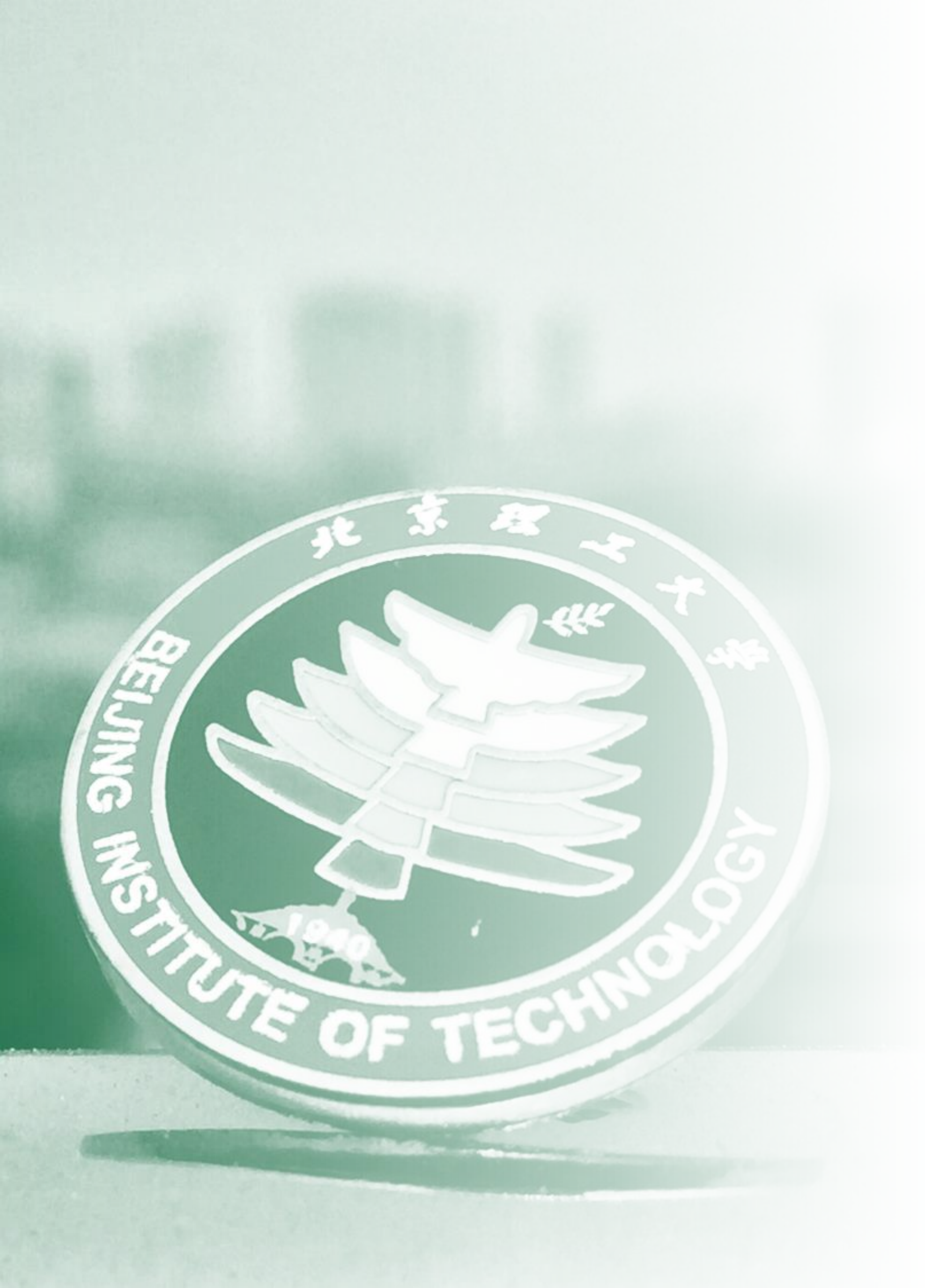


1 Research Background

Research Background

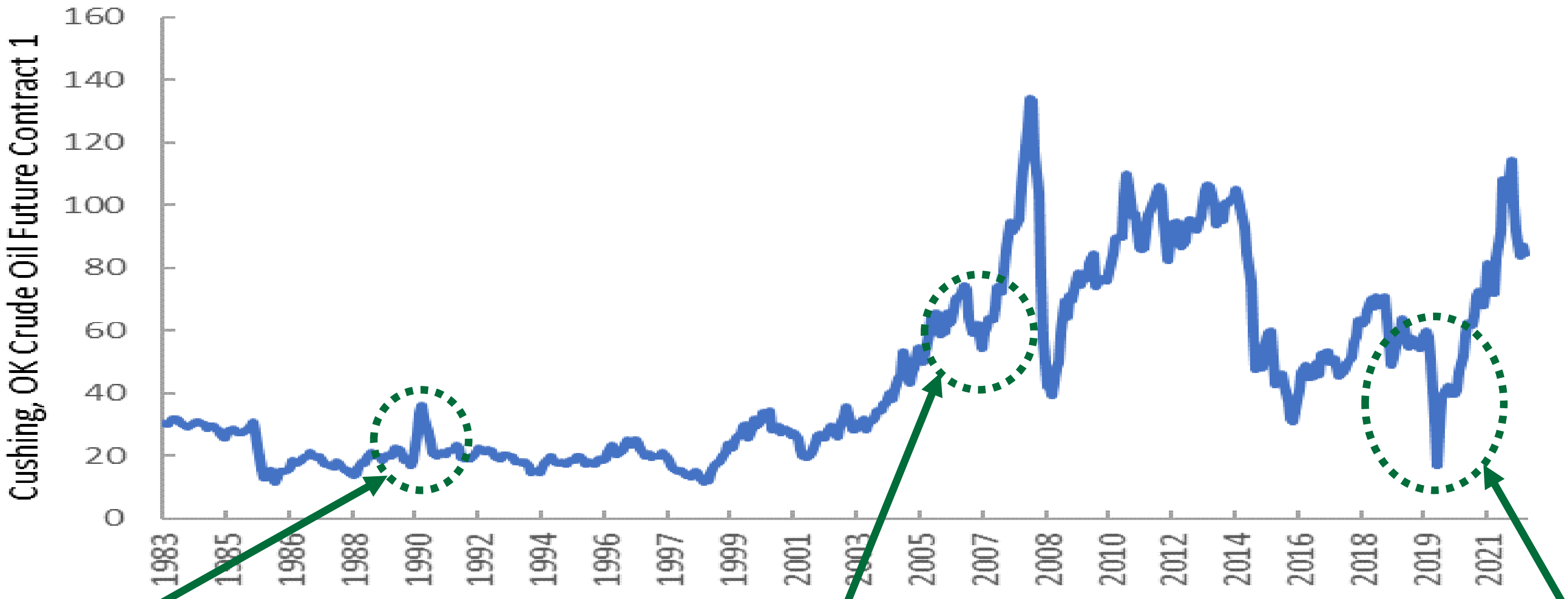


Fig.1. International crude oil futures prices.

Fig.2. The Gulf War.

Fig.3. Hurricane Katrina.

Fig.4. COVID-19 Pandemic.

- Because the dummy variables cannot describe the development process of the event, the intervention analysis method that defines the event as dummy variables will inevitably lead to information loss.

- Blair et al. introduced dummy variables representing hurricanes into the ECM model to measure the impact of hurricanes on international oil prices. (Blair et al., 2008)
- Coleman introduced dummy variables to study the impact of ten events affecting the oil market on international oil prices up to 2012. (Coleman, 2012)

Literature Review： Event Study

- **The event study method based on market efficiency is more suitable for measuring the impact of short-term events, and when major emergencies occur, it is difficult to guarantee the hypothesis of market efficiency.**

- Guidi et al. used the event study method to analyze the impact of OPEC policy changes on international oil prices and stock prices. (Guidi et al., 2006)
- Lin et al. used the event study method to evaluate the impact of OPEC meeting announcements on oil prices. (Li et al., 2010)
- Muhammad et al. assessed the impact of the Russia-Ukraine conflict on the world energy market and metal market using the event study method. (Muhammad et al., 2022)

Literature Review: Other assessment methods

- Zhang et al. used the empirical mode decomposition (EMD) method to extract the weight of major events from the oil price. However, this method has no statistical test and confidence interval, so it is difficult to judge the accuracy of its estimation. (Zhang et al., 2009)

- He et al. proposed a new prediction-based event evaluation method, which eliminates the assumption of market efficiency and can evaluate the time-varying impact of emergencies from a macro and long-term perspective. He et al. used this method to assess the impact of COVID-19 on Macau's tourism industry. (He et al., 2022)

Prediction Method： Econometrics

- **Based on the linear characteristics of data and the assumption of stationarity, the traditional econometrics method is used to forecast the energy price.**

- **Alessandro Lanz et al. used a co-integration and error correction model (ECM) to predict the prices of ten heavy crude oils and fourteen petroleum products in Europe and the Americas between 1994 and 2002. (Lanza et al., 2005)**
- **Based on the price data of Brent crude oil from November 2012 to April 2013, Xiang and Zhuang analyzed and forecasted the Brent crude oil price by using the ARIMA model. (Xiang et al., 2013)**
- **Hassan Mohammadi et al. tested the effectiveness of several ARIMA-GARCH models in modeling and predicting conditional mean and volatility of weekly crude oil spot prices. (Mohammadi and Su, 2010)**

Prediction Method： Artificial Intelligence

- **The artificial intelligence method based on machine learning has strong nonlinear processing ability, so it has been widely used in energy price forecasting in recent years.**

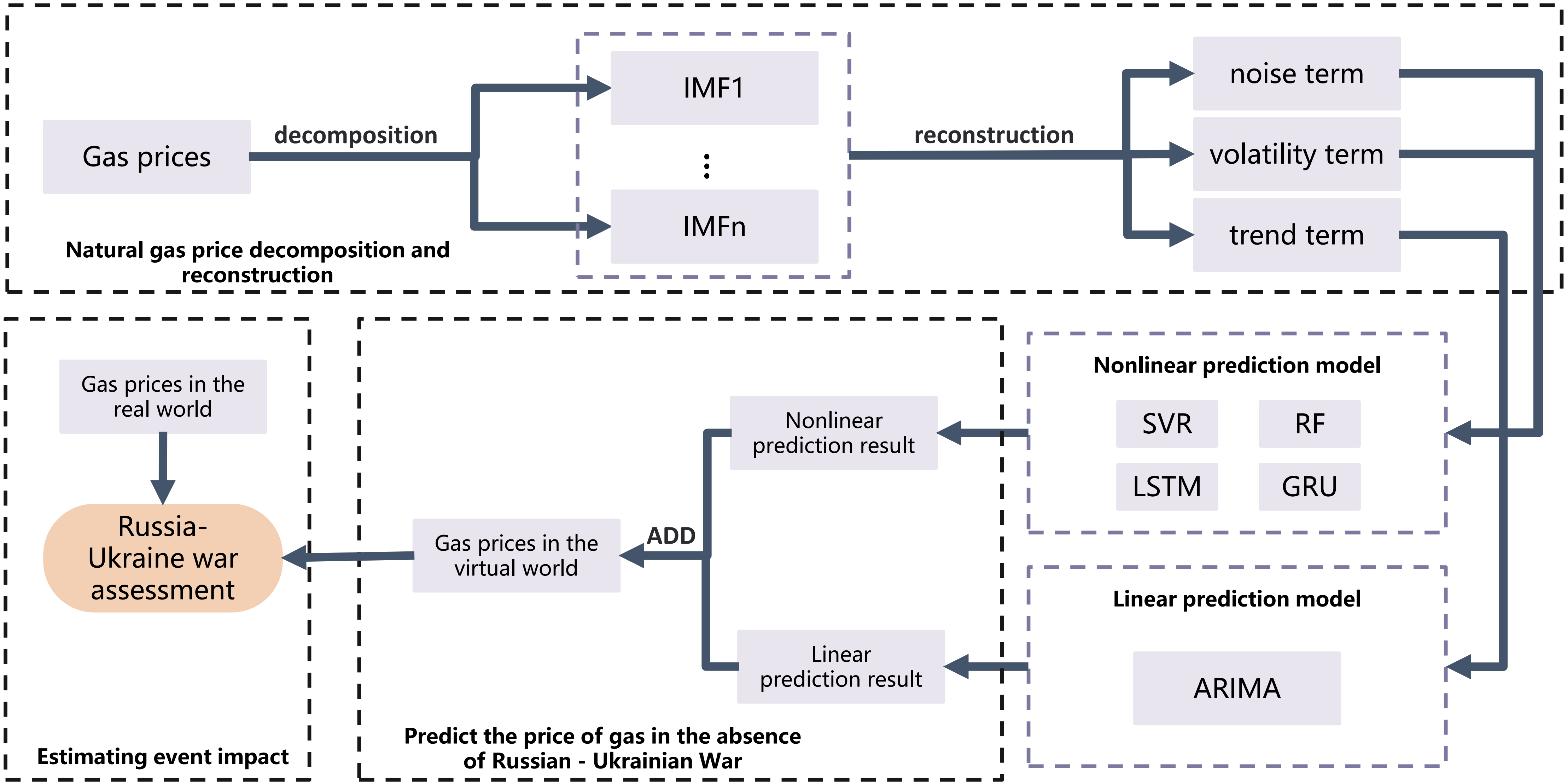
- Godarzi et al. used a dynamic artificial neural network method to predict oil prices. (Godarzi et al., 2014)
- Haruna Chiroma et al. propose an alternative approach based on a genetic algorithm and neural network (GA–NN) for the prediction of the West Texas Intermediate (WTI) crude oil price. (Chiroma et al., 2015)
- Yang et al. used a hybrid AI method to process traditional economic data and GSVI data to reflect the macro and micro mechanisms affecting crude oil prices, effectively reducing the error of crude oil price prediction from the source. (Yang et al., 2021)

- **The decomposition and reconstruction forecasting framework can improve the robustness of the forecasting model, as it can make full use of the advantages of different types of models.**

- **Yu et al. used EMD to decompose the spot price of crude oil and then used a three-layer feedforward neural network (FNN) model to model and forecast each extracted component. (Yu et al., 2008)**
- **In order to eliminate the mode mixing, Yu et al. decomposed the spot price of crude oil using ensemble empirical mode decomposition (EEMD), and used the extreme learning machine(ELM) model to ensure the validity of component prediction. (Yu et al., 2016)**
- **In order to eliminate the cumulative error, Li et al. adopted complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) to achieve the decomposition and integration prediction of China's sovereign CDS. (Li et al., 2021)**

2 Research Methods

Research block diagram



Decomposition Algorithm

Complete Ensemble Empirical Mode Decomposition with Adaptive Noise Analysis （CEEMDAN）

Method Steps：

Step1： $s_i(t) = s(t) + \varepsilon_0 \omega_i(t)$， $i = 1,2,\ldots,I$ $\overline{IMF_1(t)} = \frac{1}{I}\sum_{i=1}^{I} IMF_{i1}(t)$

Step2： $r_1(t) = s(t) - \overline{IMF_1(t)}$

Step3： $s(t)' = r_1(t) + \varepsilon_1 E_1(\omega_i(t))$ $\overline{IMF_2(t)}(t) = \frac{1}{I}\sum_{i=1}^{I} E_1(s(t)')$

Step4： $r_m(t) = s(t) - \sum_{j=1}^{m} IMF_j(\bar{t})$

Step5： $s(t) = r_m(t) + \sum_{j=1}^{m} \overline{IMF_j(t)}$

Method Advantage：

Avoid mode mixing； More effectively eliminate noise； Ensure data alignment

Reconstruction Algorithm

Sample Entropy（SE）

Method Steps：

Step1：$X_m(i) = [x(i), x(i+1), \ldots, x(i+m-1)], 1 \leq i \leq N-m+1.$

Step2：$d[X_m(i), X_m(j)] = max_{k=0,1,\ldots,m-1}(|x(i+k) - x(j+k)|)$

Step3：$B_i^m(r) = \frac{1}{N-m} B_i$

Step4：$B^{(m)}(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} B_i^m(r)$

Step5：$A_i^m(r) = \frac{1}{N-m} A_i$

Step6：$A^{(m)}(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} A_i^m(r)$ $\quad SampEn(m, r, N) = -ln\left[\frac{A^{(m)}(r)}{B^{(m)}(r)}\right]$

Method Advantage：

Calculation is independent of the data length； Effectively measure data complexity

Linear Prediction Model:

Autoregressive Integrated Moving Average model（ARIMA）：

$$X_t = \theta_0 + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q}$$

Nonlinear Prediction Model :

Support Vector Regression（SVR)

Random Forest Regression（RF)

Long Short Term Memory（LSTM)

Gated Recurrent Unit（GRU)

Analyze the impact of the conflict:

The impact of the conflict, $I(t)$, can be described as the difference between the real price $\mathrm{P}(t)$, and the forecast price $\hat{P}(t)$. That is:

$$I(t) = \mathrm{P}(t) - \hat{P}(t)$$

Analyze the degree of the conflict:

The degree of the impact $\mathrm{D}(t)$, which is considered as the average value of $I(t)$. That is:

$$D(t) = \frac{1}{t}\sum_{i=1}^{t} I(t)$$

3 Empirical Analysis

Data Source

NYMEX Natural Gas 2018/05-2022/11

Volume of data：55 Source of data：Wind

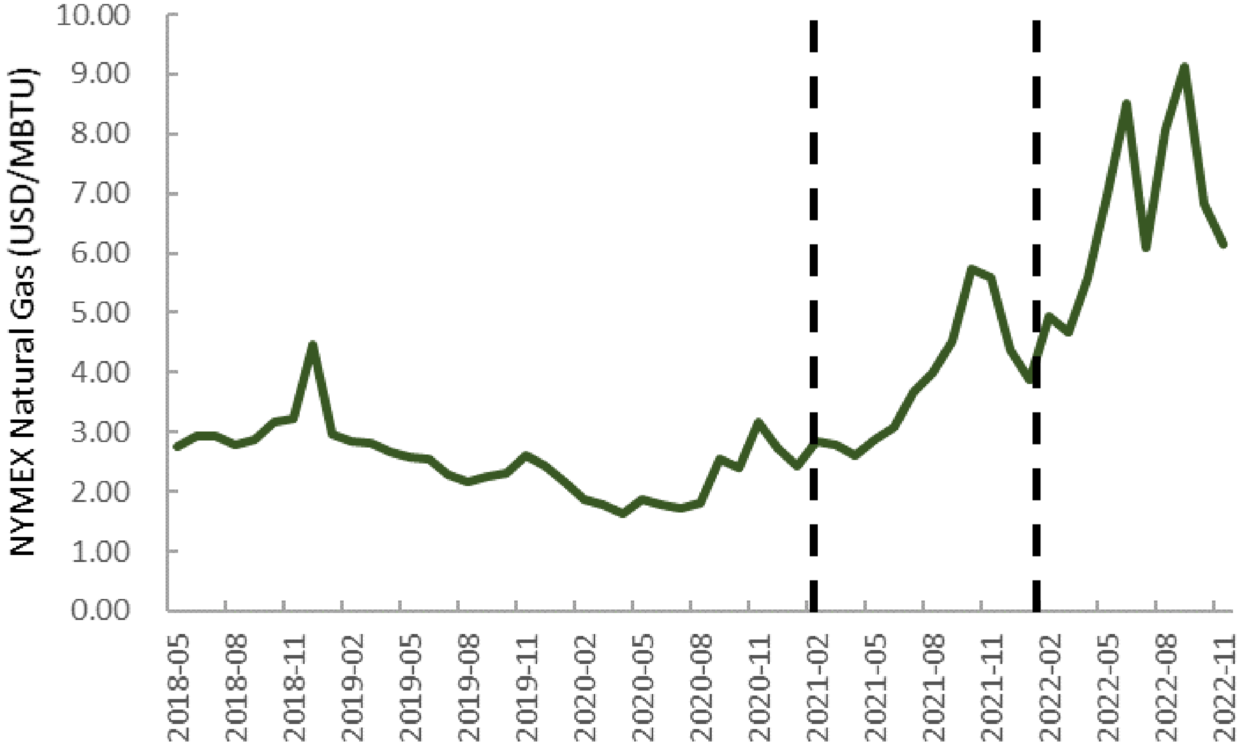


Fig.5. Raw gas price data.

Table 1 Sample period division

	Start time	End time
Train set	2018/05	2021/01
Test set	2021/02	2021/12
Forecast set	2022/01	2022/11

Natural gas price decomposition and sample entropy

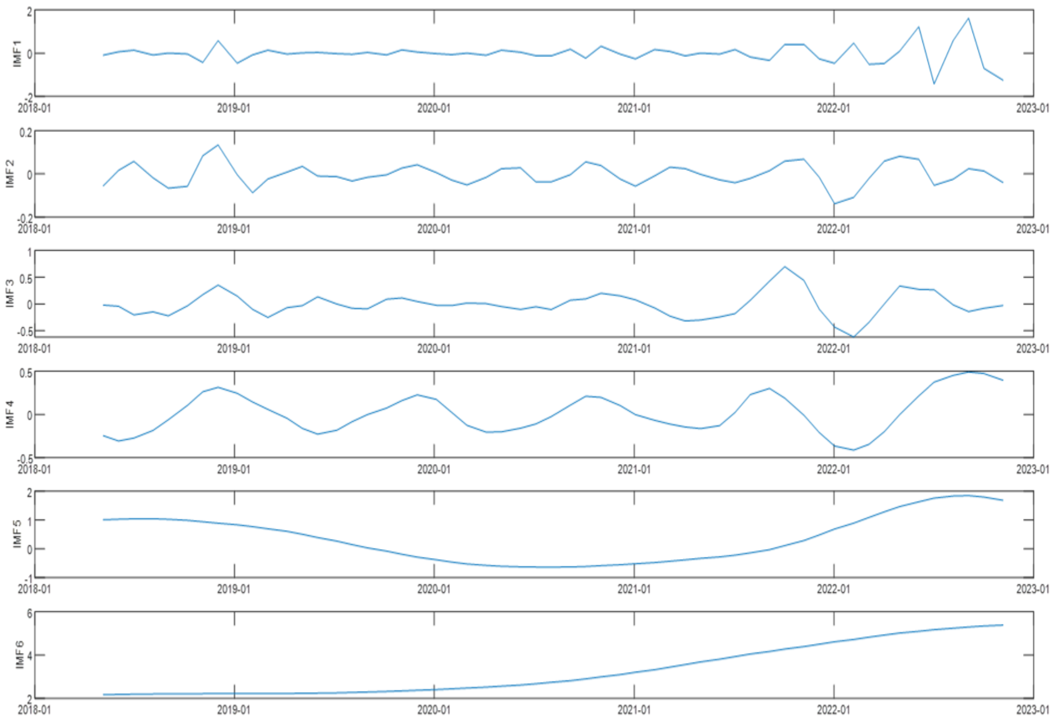


Fig.6. CEEMDAN decomposition.

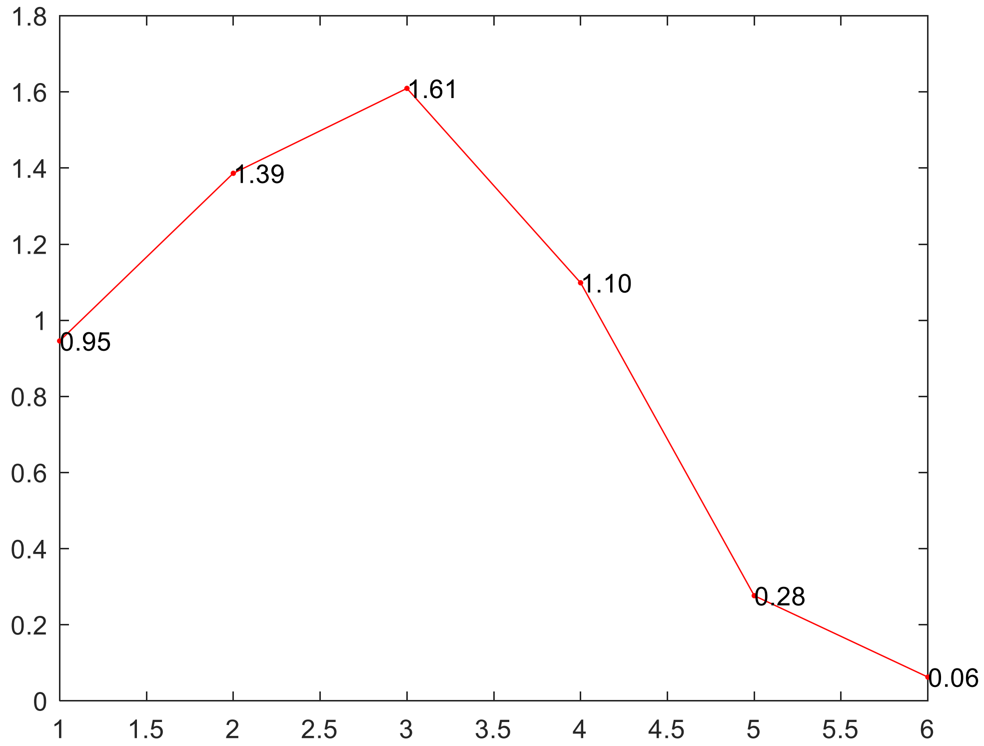


Fig.7. The sample entropy of the component.

Table 2 Result of component reconstruction.

noise	volatility	trend
IMF3	IMF1+IMF2+IMF4+IMF5	IMF6

Result of component reconstruction

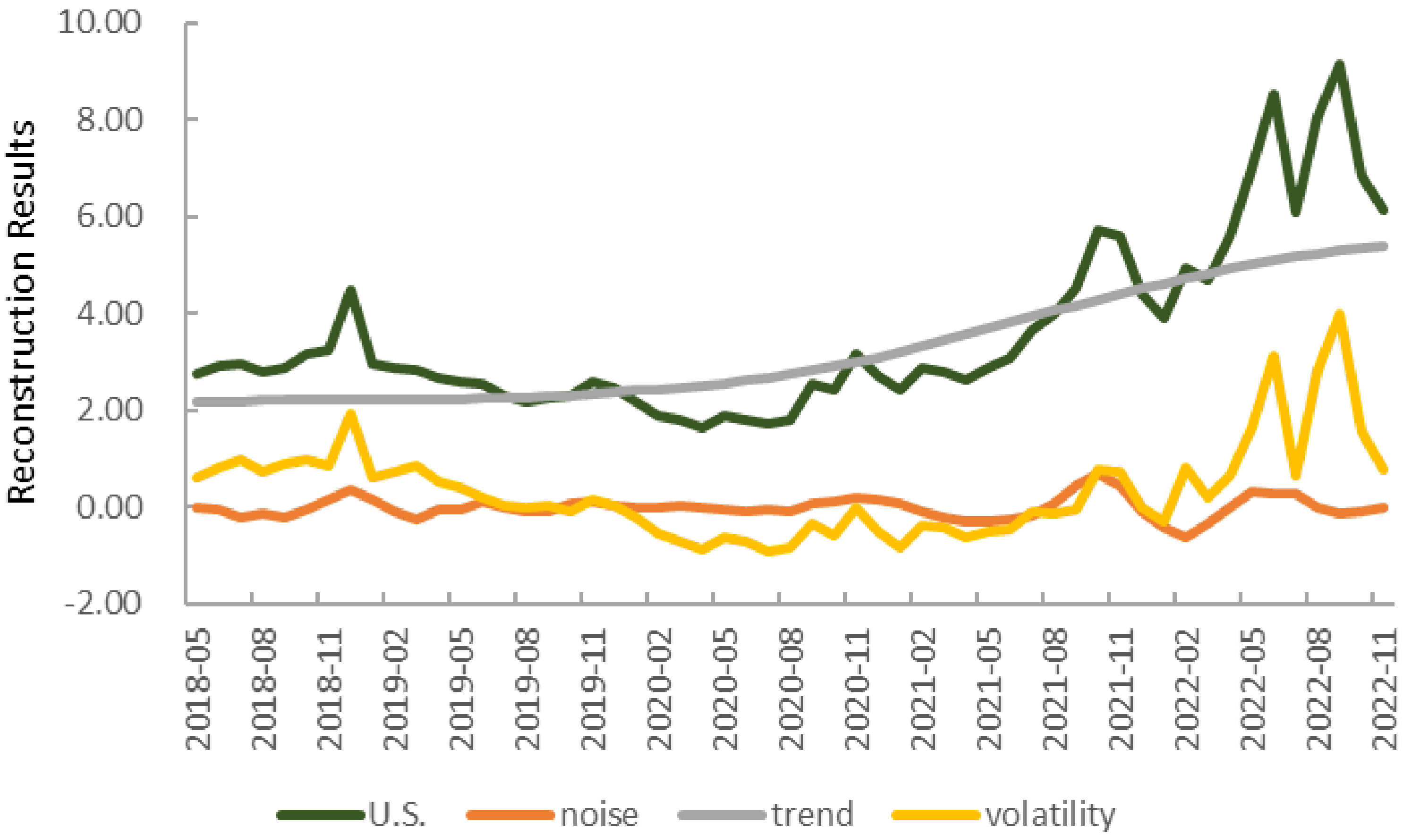


Fig.8. Result of component reconstruction based on sample entropy.

The performance on the test set of noise

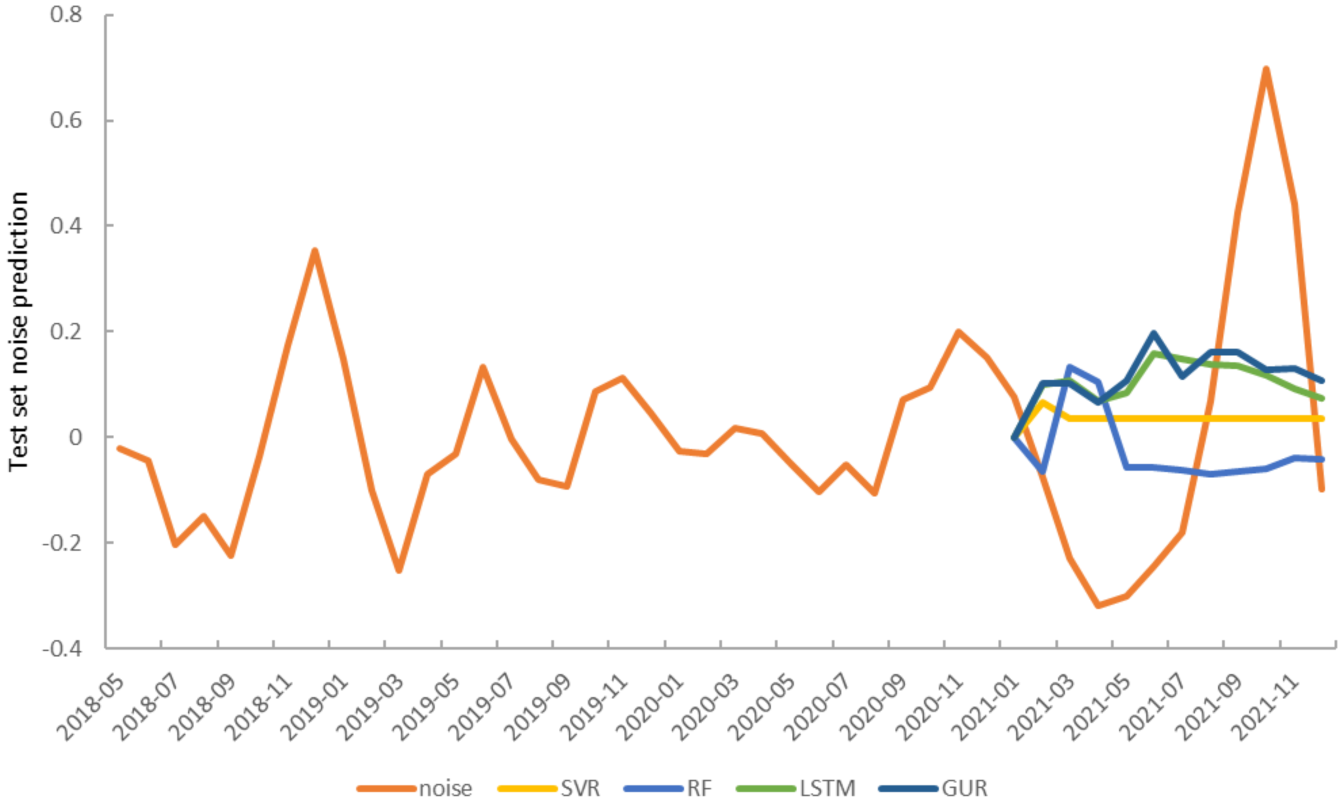


Fig.9. The performance of all models on the test set of noise.

Table 3 The performance of all models on the test set of noise.

Index of evaluation	MAE	RMSE	MAPE
SVR	0.292	0.333	1.115
RF	0.296	0.367	1.017
LSTM	0.315	0.342	1.349
GRU	0.316	0.341	1.400

The performance on the test set of volatility

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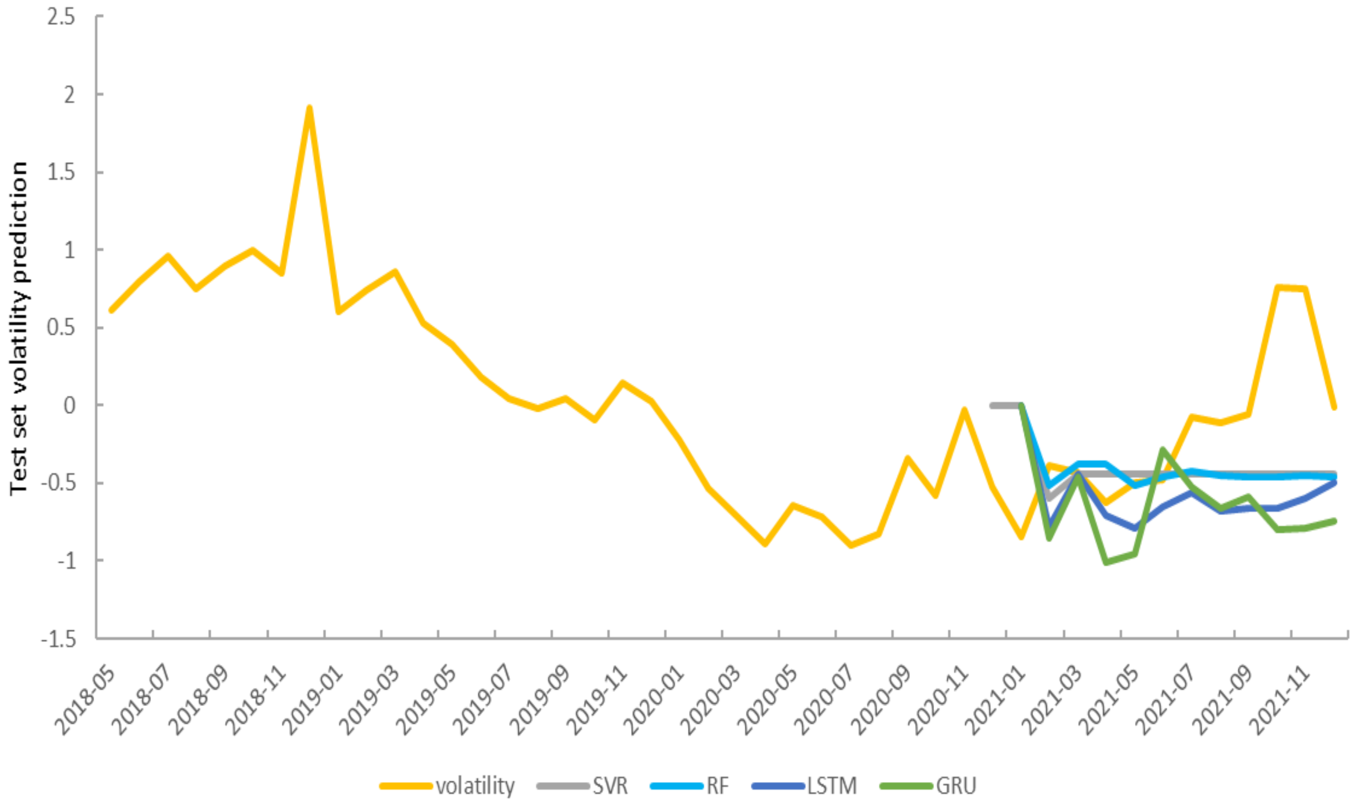

Fig.10. The performance of all models on the test set of volatility.

Table 4 The performance of all models on the test set of volatility

Index of evaluation	MAE	RMSE	MAPE
SVR	0.400	0.567	5.073
RF	0.402	0.572	5.182
LSTM	0.531	0.691	6.299
GRU	0.626	0.783	8.175

The performance on the test set of trend

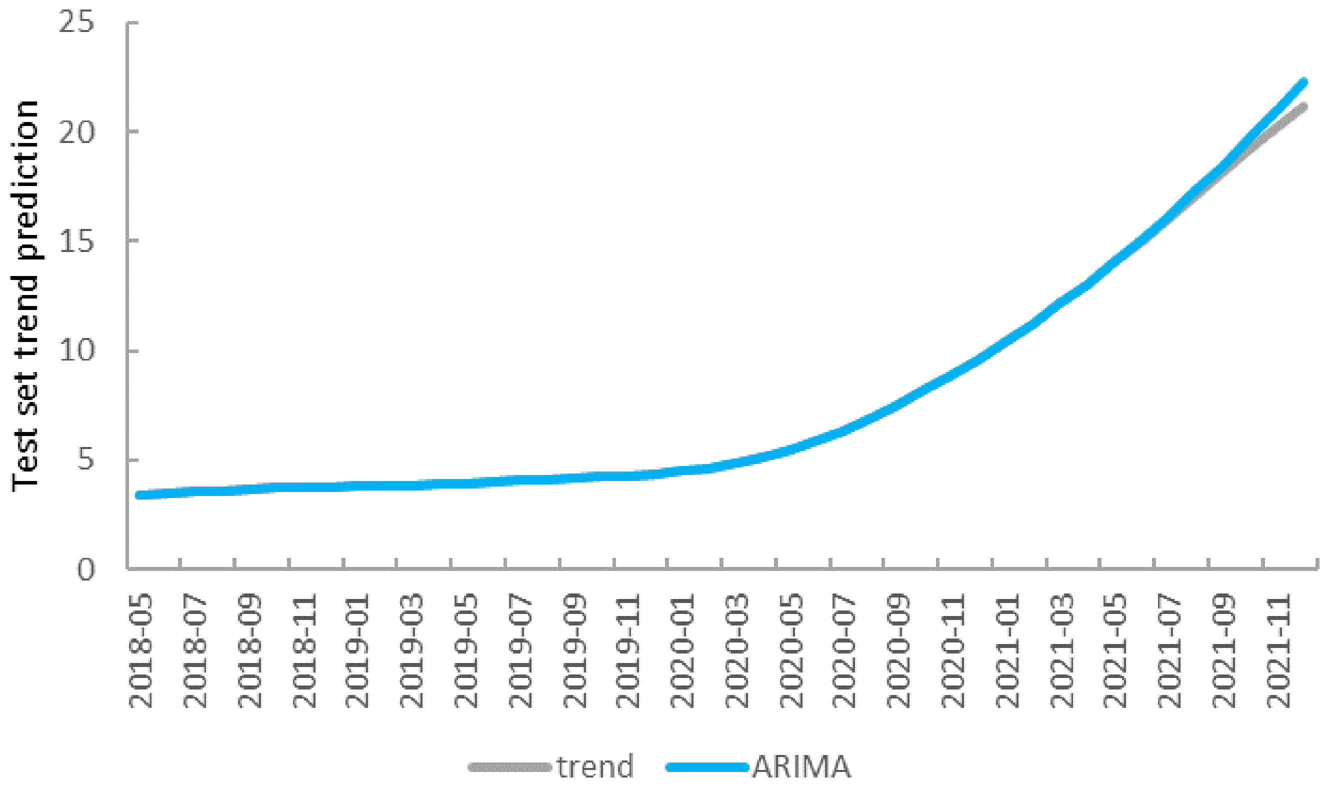

Fig.11. The performance of all models on the test set of trend.

Table 5 The performance of all models on the test set of trend

Index of evaluation	MAE	RMSE	MAPE
ARIMA	0.277	0.447	0.014

Comparison between D&R and reference method

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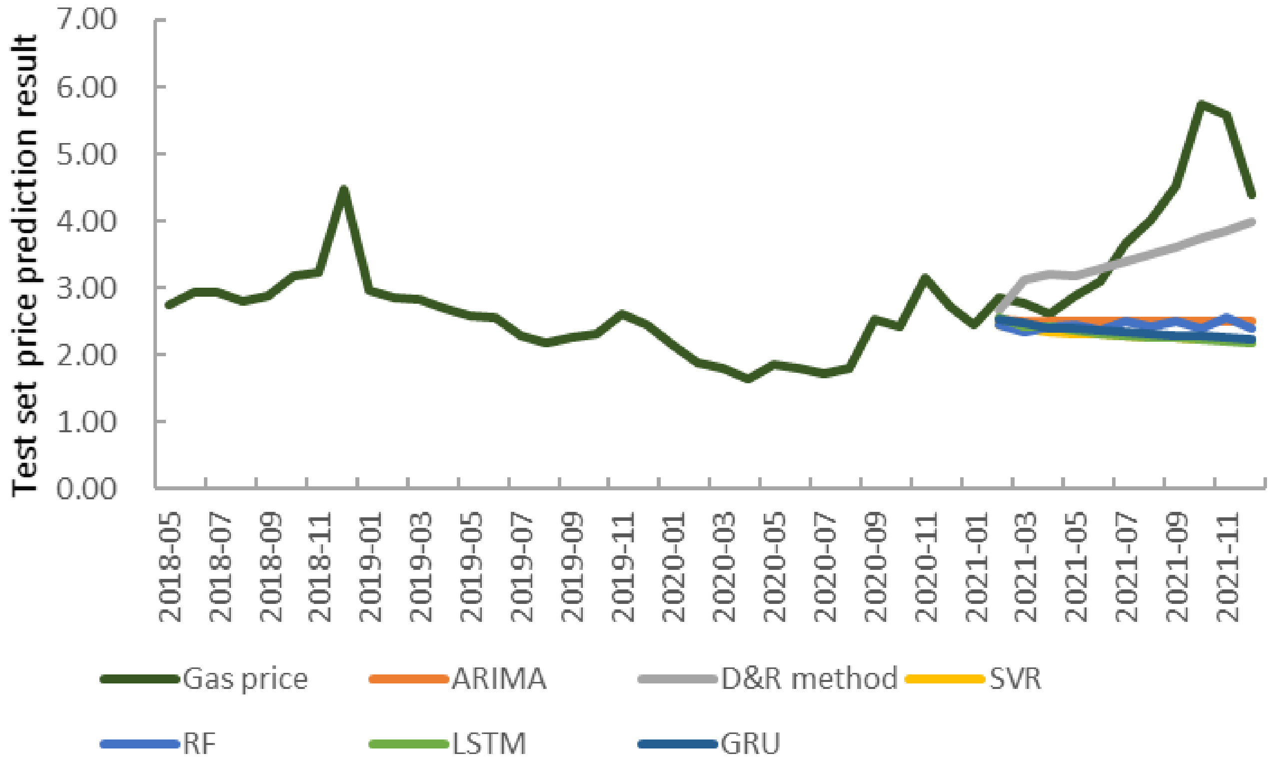

Fig.12. Comparison between D&R method and reference method.

Table 6 Comparison between D&R method and reference method

Index of evaluation	MAE	RMSE	MAPE
D&R method	0.678	0.903	0.158
ARIMA	1.321	1.701	0.295
SVR	1.533	1.902	0.350
RF	1.396	1.743	0.317
LSTM	1.510	1.902	0.342
GRU	1.482	1.868	0.335

Construct a virtual world without conflict

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Fig.13. The prediction result of the deconstruction and reconstruction framework.

The impact of Russia-Ukraine conflict

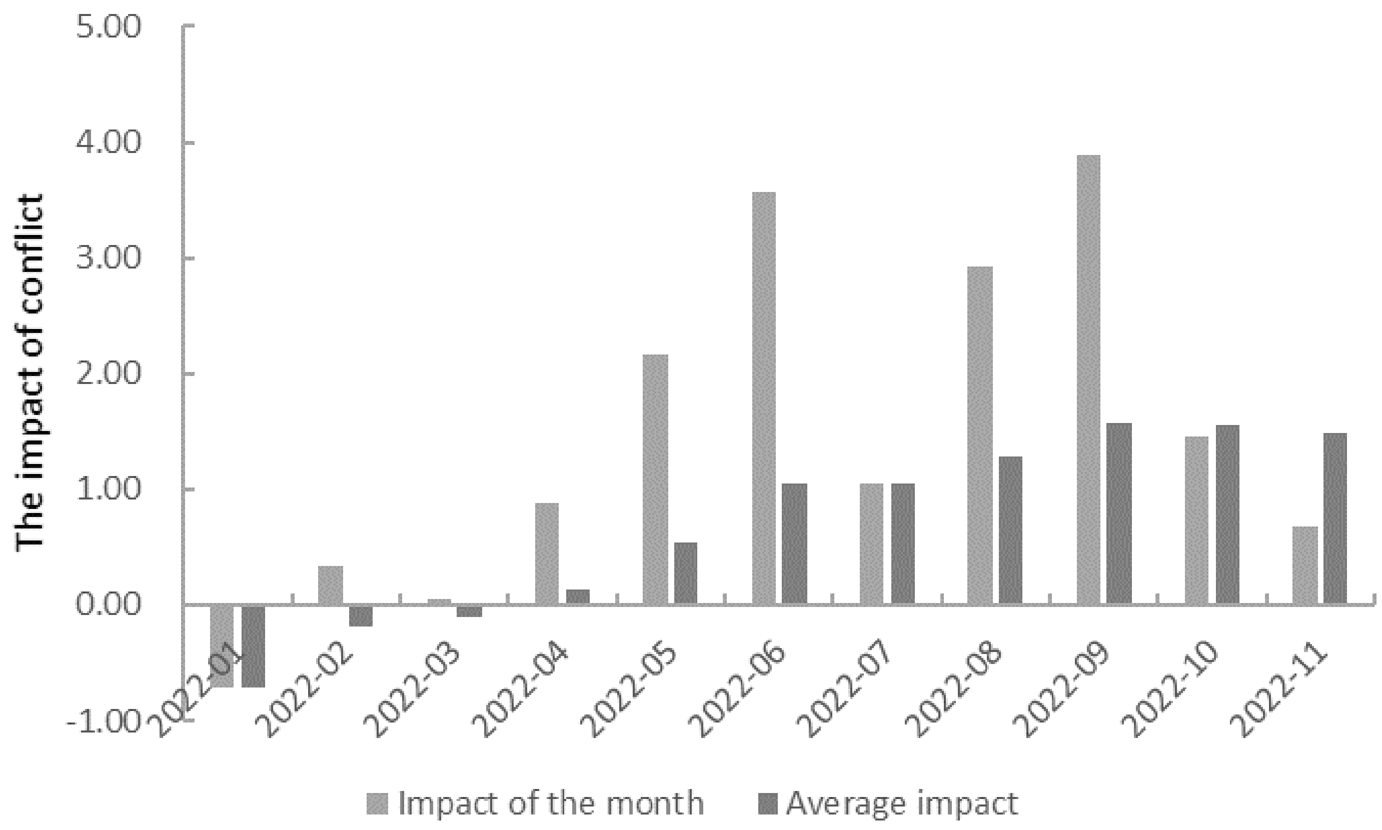

Fig.14. Schematic diagram of incident assessment results.

- **Russia-Ukraine conflict hit gas markets hardest in June and September.**
- **The impact of the conflict on the world gas market began to be felt in May.**
- **The Russia-Ukraine conflict caused gas prices to rise by 22.97% in 2022.**

4 Conclusions

Conclusions

- **Compared with the benchmark models, the decomposition and reconstruction model showed better performance in the multi-step gas price prediction, and its MAPE increased by about 13 percent.**
- **The influence of Russia-Ukraine conflict in different months is heterogeneous. For a single month, the Russia-Ukraine conflict had the biggest impact on gas prices in June and September.**
- **From the average impact, there is a certain lag, and the impact of the conflict will not be clearly shown until May 2022.**
- **Overall, the Russia-Ukraine conflict caused gas price to rise by about 20 percent in 2022.**

Thanks